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Abstract – This paper discusses the successes and failures over the past three years as efforts at the Idaho National Engineering and Environmental Laboratory (INEEL) have developed and evaluated robot behaviors that promote the emergence of swarm intelligence. Using a team of 12 small robots with the ability to respond to light and sound, the INEEL has investigated the fundamental advantages of swarm behavior as well as the limitations of this approach. The paper discusses the ways in which biology has inspired this work and the ways in which adherence to the biological model has proven to be both a benefit and hindrance to developing a fieldable system. The paper outlines how a hierarchical command and control structure can be imposed in order to permit human control at a level of group abstraction and discusses experimental results that show how group performance scales as different numbers of robots are utilized. Lastly, the paper outlines the applications for which the resulting capabilities have been applied and demonstrated.

I. INTRODUCTION

At the Fifth International Symposium on Distributed Autonomous Systems (DARS 2000), Lynn Parker discussed the current state of the art for the field of distributed autonomous mobile robots [1]. This paper outlined the research progress which had been made in many areas, but also spoke of the open areas of research which included how to identify and quantify the fundamental advantages and characteristics of multi-robot systems; how to enable humans to control multi-robot teams; how to scale multi-robot behavior to large numbers of robots and how to enable physical robot systems to cope with difficult real-world environments. In 2000, these were among the most pressing issues facing the field of distributed robotics. How far have we come since then towards answering these questions? The goal of this paper is to show how, since that time, efforts at the INEEL have provided unique responses to those open research questions.

The INEEL approach embraced the idea of inexpensive, disposable robots that communicate implicitly with light and sound, using the environment, rather than internal state, as the basis for coordination. The expression 'swarm intelligence' was first used by Beni to describe systems where many simple agents generate patterns and self-organize through nearest neighbor interactions [2]. More recently, Bonabeau, Dorigo and Theraulaz have supplied a useful definition of the term as "any attempt to design algorithms or distributed problem-solving devices inspired by the collective behavior of social insect colonies and other animal societies." [3] Borrowing on work by Tsetlin we can identify four main characteristics of swarm behavior including randomness, decentralization, indirect interaction, and self-organization [4]. Throughout this paper, we discuss how each of these ingredients impact performance of our robot collective.

When compared with traditional approaches, swarm intelligence offers the potential for tremendous gains in terms of cost, fault-tolerance, and overall performance. However, we have also found ourselves faced with difficult questions especially pertaining to tasking and operational deployment. For all their remarkable effectiveness, ants and bees are not easy to predict, control or task. Building swarm intelligence may provide robustness, but it makes things quite difficult for both the developer and the human user. For instance, how do we debug individual robot behavior when we cannot communicate semantically with the individual robots? If no individual robot understands the entire task or environment, how can we insure or even promote an optimal solution? We want swarm behavior that is adaptive, self-regulating and non-deterministic. Not surprisingly, the resulting system is difficult to predict. How do we provide performance guarantees or train operators for such systems? Clearly, swarm intelligence is not a universal remedy for the hard problems of multi-robot coordination.

Despite these challenges, our efforts to develop swarm intelligence have proved successful on a variety of fronts. We have shown how the benefits of swarm intelligence can be maximized by using a reactive implementation of social potential fields. We have shown how to curtail the detrimental effects of swarm behavior through online learning. By adding multi-modal communications, we have mitigated the limitations of implicit communication. To address the need for user tasking, we have developed a hierarchical command and control structure, which utilizes specialized robots as sergeants. Finally, we have shown how the resulting swarm behaviors can be harnessed to reliably accomplish real-world task functionality including exploration, spill finding and perimeter formation.

II. BENEFITS AND LIMITATIONS OF BIOLOGICAL APPROACHES

Many distributed robotic efforts pay homage to the ideals of behavior-based control, which emerged in the mid to late 1980's [5,6]. The resulting focus on embodied, situated intelligence has informed much multi-robot work and draws heavily from biological inspirations [7,8,9]. Despite this heritage, most multi-robot endeavors continue to rely on sophisticated internal states, directed, explicit communication, and accurate position information – the hallmarks of contemporary robotics. Instead, our approach to creating swarm intelligence employs entomologically inspired modes of perception allowing the robots to respond to sudden changes in light, chirping, antennae-like touch sensing and moisture detection. The resulting robots do not form reliable communication networks and they cannot pass complex semantic information to one another. Nor can they maintain an internal representation of their environment.

In our own work, we found that in order to reap the benefits we see in insect communities, we were forced to take on many of the disadvantages as well. Ants cannot provide reports on what they are doing, nor can they respond to varying kinds of high-level tasking. An ant searching for food does not employ optimal coverage algorithms, but rather spends much of its time wandering. Likewise, with our experiments, we found it necessary to focus on group behavior rather than the performance of any given individual as it navigates a world of light and sound gradients unseen by human eyes. Is this really the kind of robot we want? Certainly, there are limitations to the tasks for which such resource constrained robots will be appropriate. Failure to acknowledge these limitations and choose appropriate tasks will greatly reduce the opportunity for small-scale distributed robots to be successfully deployed. On the other hand, despite their limitations ants can effectively perform a surprising array of complex tasks.

III. MOTION COORDINATION

One of the most common areas for study in the field of distributed robotics is the problem of how to control the movement of large numbers of robots effectively. Studies have been performed in multi-robot path planning [10], traffic control [11], and formation generation [12,13,14]. Across the many social communities we find in nature, we find a fascinating ability for populations to form and maintain collective patterns. These patterns are formed by the animal's ability to remain close to the flock and yet also avoid collisions and other problems of overcrowding [15]. Within the flock, the bird does not know the position of all others in the flock, but rather adjusts its position by responding to its immediate neighbors. Likewise, our design approach was to create a simple set of individual behaviors, which allow each robot to sense and react to its immediate neighbors. Building on work by Reif and Wang [16] and Dudenhoeffer and Jones [17], we chose to investigate the possibility of using social potential fields as the primary means to coordinate group behavior.

The first step was to develop a simulation program, AgentSim, that allowed us to create different individual robot behaviors and then observe the emergent results. As we investigated the effects of social potential fields, this simulation of large-scale robot interaction offered key insight. Using AgentSim, we found that the social potential field strategy provides the swarm with a means to automatically regulate itself. Moreover, simulation showed the potential for a user to control swarming

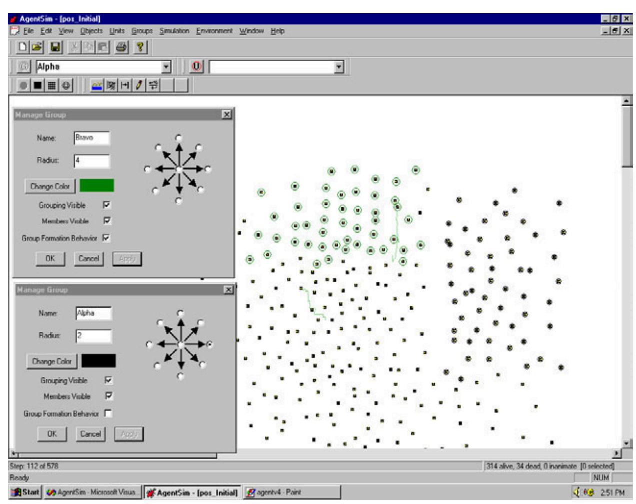

Fig 1. AgentSim

behavior at a high level by modulating the attractive and repulsive arms of the social potential fields.

Although simulation allowed us to understand the effects of social potential fields in principle, it ultimately could not provide the fertile soil of chaotic, real-world physics necessary for swarm intelligence to reap its full rewards. In regard to their own work with simple, stigmergy-based robots, O. Holland and C. Melhuish explain, "… it seems very likely that the richer the physics, the simpler the behavior can be." [18] In an attempt to move closer towards this form of organic real-world sensing, the INEEL developed a real world robot team of robots with touch sensors, photo-resistors, microphones, and IR sensors.

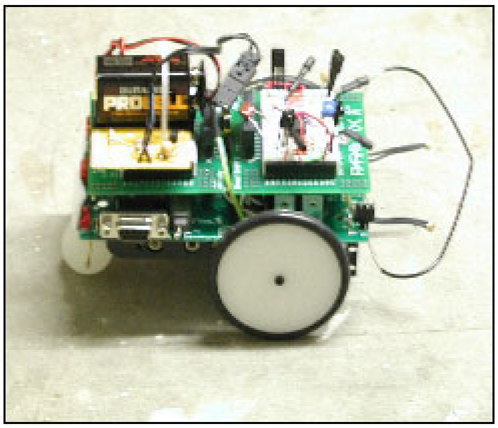

Fig. 2. Robot with microphones, spill sensor, infrared break beams, bump and light sensors.

The goal was to create reactive behaviors with as tight a coupling between sensing and action as possible. Within this embodied approach, the robots respond to fluctuations in sound and light that are caused as they approach or are approached by other entities including other robots as well as obstacles and walls. In addition, the robots have the ability to emit and respond to audible "chirping" that can be used to attract and repel other robots. In fact, the behaviors we developed for area searching, obstacle avoidance and perimeter formation all depend on the robot's ability to respond to this acoustical implementation of social potential fields.

While our implementation of social potential fields offers dividends in terms of scalability, robustness, domain-generality, and decentralization, it also presents some difficult challenges. In cluttered environments, the robots often respond to echoes reverberating off of walls and may have some difficulty localizing the source. Like real insects, the robots are not aware of whether a light fluctuation is the result of another robot, a human onlooker or an obstacle. To those observing the behavior of the swarm, individual robot is often inexplicable.

IV. LEARNING

Early on, we noticed that small variations in the placement and sensitivity of the robot's sensors and actuators can produce overweening behavioral effects, often emerging in unpredictable ways from the compounding interactions between robots. Emergent effects are not necessarily helpful and it was not long before we discovered that swarm behavior can be counterproductive. To a point, close-knit robot interaction can be beneficial, especially in pushing the robots into unexplored, hard to reach areas. However, if the density of robots rises too high in a given region, the robots begin to exhibit detrimental forms of interaction. Without a means to regulate the robots' responsiveness to light and sound fluctuations, the robots would often turn in place attending to every facet of the environment or, at other times, would entirely fail to respond to obstacles and other robots. Before we could realize the advantages of swarming behavior, we needed some means to reduce redundancy and interference by adapting individual robot behavior to different environments and varying numbers of robots.

Many researchers believe that learning is the key to enabling effective swarm behavior and have utilized it for tasks ranging from box pushing to playing soccer [19, 20, 21]. However, our simple, unintelligent robots do not have the computational power to learn anything as sophisticated as a cooperative strategy. We did, however, have a need for the robots to exhibit some form of self-regulation. Within our implementation, positive and negative feedback are supplied by an internal critic that is invoked at regular time intervals on each robot. The critic continually adjusts sensitivity to light and sound fluctuations to insure that the robots are each able to respond productively to their surroundings. With this online parameter adjustment system in place, we found that perception of real world light intensity and sound fluctuations offers a perfect means to draw an appropriate level of randomness – a key component of swarm behavior -- into the robots' behavior. By adjusting the level of randomness, the online learning system can modulate certain emergent properties of the swarm and provide a means to adapt the swarm to new environments.

V. SEARCH AND EXPLORATION

The resulting motion coordination based on self-adjusting social potential fields was sufficient to produce a rudimentary form of swarming behavior. Given a critical mass of robots in a given area, swarming behavior naturally emerged and became self-sustaining. We now needed some way to measure the performance of the swarm and relate it to the performance of a single robot. Our immediate goal was to show that the social interactions produced by our implementation of social potential fields could produce beneficial emergent effects.

Unfortunately, few performance metrics exist for assessing the performance of multi-robot systems. Although some excellent work has been done to study the challenges of getting many robots to cover a large area, there have been surprisingly little work that has taken swarm intelligence to task on real-world coverage experiments [22,23,24]. Sukhatme, Balch and Parker have suggested various means to quantify and compare performance of multi-robot systems [25, 26, 27]. There is, however, little consensus on how to empirically measure emergent effects in populations of real robots. Ronald et al. have argued that the absence of a definition for the word ‘emergence,’ has produced misunderstandings and generally diluted the meaning of the word [28]. Ronald et al. suggest an *emergence test* that involves evaluating individual behaviors, observing global effects and then cataloguing the difference between expectations based on individual behavior design and the observations of actual global results.

For our purposes, we needed some means to quantify benefits of swarm intelligence in reference to individual robot behavior. We decided to compare the overall performance of the real swarm (global results) to a projected linear performance curve (expectation) generated by multiplying the performance of a single robot (individual behavior) by the number of robots. In other words, we wanted to compare the performance of the real swarm, which includes social interaction, to a theoretical benchmark that takes no interaction into account. The projected line (see Figure 3), Pf(1) * n, where Pf(1) is the performance of one robot and n is the number of robots, assumes that each robot has a potential field of zero. Each robot would then be a ghost to every other. Intuition told us that we should see performance improve for each robot we added. But would the performance of the real robot swarm be above or below the linear projection? Where might the graphs intersect?

The graphs shown in Figure 3 and Figure 4 are the result of a coverage task where different numbers of robots were used to see how long it would take for complete coverage of a 64 square foot test-bed. Dry-erase markers attached to each robot allowed us to visually ascertain “ground-truth.” Coverage was deemed complete when no space remained into which a robot could fit. We ran five trials with one, two, three, four, six and nine robots. For each trial the robot(s) were placed in the same corner and were all started within a few seconds of each other. For these experiments, performance was measured as the reciprocal of time necessary to complete the task. For further discussion see Bruemmer et al. [29].

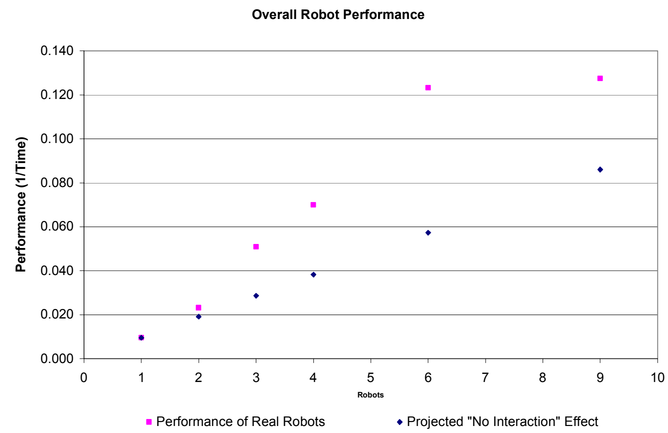

Fig. 3: The performance of the robots and the projected linear effect produced by multiplying the performance of one robot by n.

According to the “emergence test” discussed above, it is possible to measure the effects of emergent behavior by contrasting the real global results and the expectation based on individual behavior. Within Figure 3, the effect of emergent behavior would then correspond to the difference between the two curves. As we move up in number from one robot, the beneficial effect of emergent behavior increases as the two curves diverge. However, by nine robots, the difference between expectation and global results has decreased, indicating that the beneficial effect of swarm behavior has begun to diminish.

We can also present the data in terms of real performance / the number of robots. Figure 4 shows the system performance for each trial divided by the number of robots used.

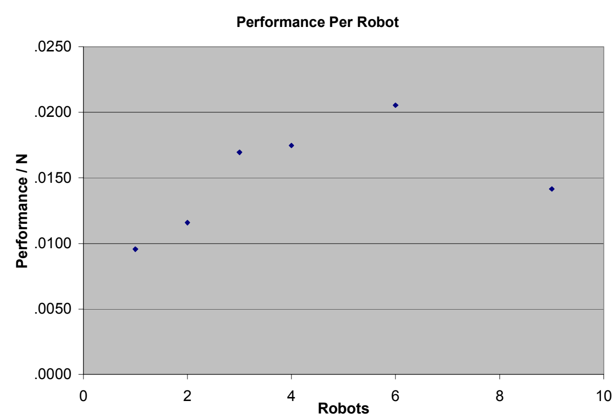

Fig. 4: The average performance for each set of trials divided by n.

Figure 4 shows that the performance per robot augments through six robots but then begins to diminish. Although much more experimentation is necessary, it certainly seems that the benefits of swarm intelligence are available only within a window of opportunity. We hypothesize that the dimensions of this window are defined in relation to the number of robots and the size of the environment.

VI. SPILL FINDING AND PERIMETER FORMATION

The goal of our efforts is to provide a robotic system that can be sent into hazardous DOE environments to perform remote characterization tasks. Many such environments are filled with piping and other clutter, making it an appropriate task for a swarm of small robots. To demonstrate that the swarm could actually accomplish a useful real-world task, we focused on developing the ability to find and form a perimeter around a liquid spill. We equipped the robots with sensors that allowed them to identify a pool of liquid on the ground and then worked to develop a behavior that allowed the robots to attract other robots to a spill once they had found it.

The challenge was that due to the constraints of the swarm approach, we had to accomplish this with no positioning, explicit communication, centralized control or internal representation of the environment. Fortunately, the effects of social potential fields proved up to the task. By increasing the volume of the tone emitted by a robot, we can also increase the attractive force of the social potential field, allowing a robot that has found the spill to draw other robots to the spill. Once a robot approaches, the repulsive arm of the social potential field insures that the incoming robot does not approach too closely. In this fashion, each robot is forced to find its own place around the spill. As soon as a robot has settled on a spot, it too begins to emit a “come hither” call that augments the overall attractive force.

The resulting behavior has been demonstrated both within the NIST Urban Search and Rescue test-bed and also within an exhibition arena at the 2001 AAAI Mobile Robot Competition and Exhibition [30]. In an area of approximately 100 square ft., informal experimentation showed that the robots are consistently able to find and form a perimeter around the spill(s) within several minutes. However, this behavior is not accomplished in an systematic or consistent manner. The robots pull a high degree of randomness from the environment in the form of light and sound fluctuations. Although a “come hither” chirp exerts a definite influence on the other robots, this influence can be temporarily subsumed by higher priority behaviors invoked by the presence of another robot or obstacle. Even the noise of the robots’ wheels and shadows caused by onlookers can factor into the behavior of the robots.

Moreover, the use of online adaptation means that although the robots all begin with the same program, each robot soon acquires a unique sensitivity based on its own experiences. This diversity can be useful in ensuring coverage over a large, varied area. However, it also makes it difficult to predict exactly how a particular perimeter formation scenario will unfold. The spill-finding and perimeter formation behaviors inevitably prevail, but never in an optimal fashion. This was, at least for us, the price to be paid for using fully distributed control and implicit communication.

Over the course of these experiments, we witnessed some interesting effects emerging from the implicit interactions of the individual robots. Due to the additive properties of sound, the attraction force of the robots that have already found the spill extends as more robots find it. This provides a rudimentary form of peer validation. If a robot mistakenly identifies a plume, the attractive force will remain small since other robots will not augment the sound. One effect that we had not expected was that the repulsive effects of the social potential fields also grew as robots began to form a perimeter, making it increasingly difficult for each additional robot to get onto the spill. When two separate small spills were used, the combined repulsive field of the robots that had already formed a perimeter around the first spill prevented additional robotic resources from being spent on the already marked spill. Instead, the strong repulsive arm pushed the remaining robots away from the first spill, allowing them to seek out the second. On the other hand, when there was only one large spill, all the robots were able to find a place around the perimeter of the spill -- the repulsive arm extended only far enough to force robots around the perimeter.

VII. HUMAN TASKING AND CONTROL

A key element in the transition from tabletop development to field deployment is the role of the human operator and the necessary interaction between the robotic force and human during the mission. The words that General Bruce C. Clarke stated in 1959 hold true with regard to the introduction of robotics in military and non-military applications: “The truth is that the most expensive weapon that technology can produce is worth not an iota more than the skill and will of the man who uses it.” [31] The successful use of large numbers of robots in field applications depends on the ability for human operators to interact with the robot force, exchanging information, providing direction, and gaining an understanding of the intent and operations at both the microscopic and the macroscopic levels.

For large numbers of robots to be deployed as viable force, human users must be able to interact with functional units, rather than issuing commands to each individual robot. In order to promote user tasking and control, the INEEL adopted a hierarchical method of group abstraction whereby the operator chooses group membership and then interacts with the group leader. The operator may make this choice based on proximity or based upon functionality. The resulting tool, AgentCDR, is an operator control unit for interacting with and deploying robotic forces (see Figure 5). AgentCDR includes advanced C2 support including visualization tools, iconographic representation of robots, GUI controlled group assignment, operation planning tools, and system status alerts.

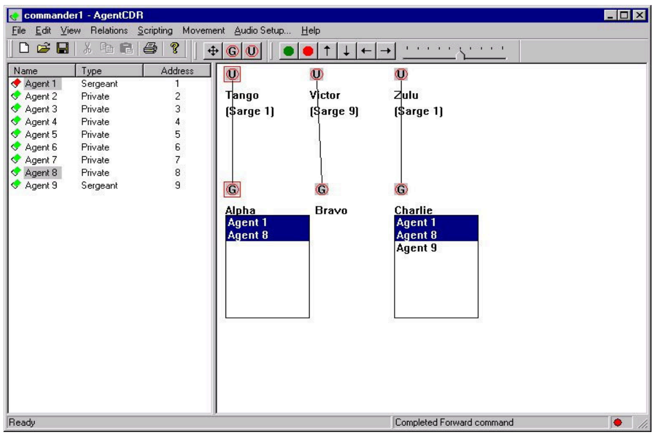

Fig. 5. AgentCDR in control of nine robots including two sergeants and seven privates.

The tasking capabilities available through AgentCDR would not have been possible without the development of "sergeant" robots which can receive radio messages from AgentCDR and pass them on to the "privates" using nearest neighbor IR communications. Although this hierarchical approach differs from the strict model of decentralization, hierarchical control is certainly present in biological swarms. For instance, a queen ant or bee is able to exert a powerful influence in order to direct collective behavior within the swarm [32]. Within our implementation, the benefits of decentralization are preserved due to the fact that privates are not dependent on the sergeants or on the human operator for continuous communication and can function autonomously in the absence of user input. This flexibility supports mixed initiative control and allows AgentCDR to balance the needs and limitations of the robots, and the human operator.

VIII. CONCLUSION

Although possibly limited in individual capability, robots deployed in large numbers could represent a tremendous cumulative force. Swarm intelligence offers a powerful mechanism for coordinating such large groups of resource-constrained robots. However, the observations given in this paper indicate that there may also be significant limitations. Perhaps the more we incorporate insight from the insect world, the more willing we must be to accept insect-like limitations.

Currently, the INEEL is faced with the challenge of how to harness the swarm intelligence behaviors that we have developed towards a useful operational capability. Towards this aim, the INEEL has demonstrated that AgentCDR can effectively deploy and task a team of cost-effective, small robots to find and converge upon a mock spill within a DOE regulated facility at the INEEL. Figure 6 below shows the results of a test deployment. Four robots have already formed a partial perimeter, while a fifth, partially visible on the far left, attempts to find its way onto the spill.

Fig. 6. Robots deployed in a cluttered DOE facility form a perimeter around a water spill.

The swarm behaviors discussed are not limited to spill finding or perimeter formation. We envision the robotics technologies developed in our research being used to map and characterize buried waste sites; to perform routine inspection and monitoring of critical components; and to provide remote characterization in the event of a hazardous spill or radiation leak. A current limitation for applications of swarm intelligence is the lack of small scale, inexpensive application-oriented sensors. One possibility that we have explored is the use of a small radiation sensor as shown in Figure 7. This sensor costs less than $300 and draws very little power. The sensor has been tested here at our desert site on three different radiation sources with favorable results. We believe that sensors such as these can permit distributed robot systems to reduce cost, increase performance and remove workers from the dangers of radioactive or hazardous materials. Paramount to realizing these benefits is the construction of robust robot behaviors coupled with human operator interface systems that facilitate human interaction.

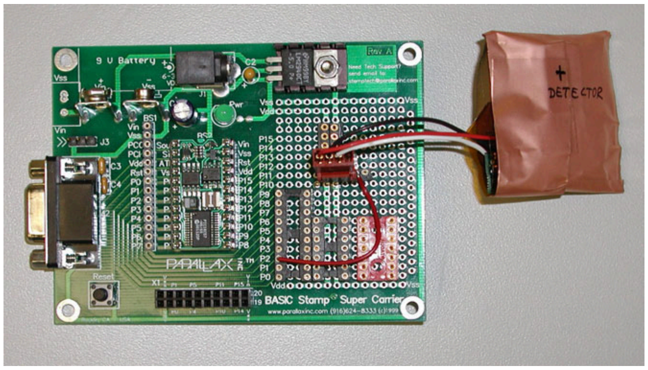

Fig. 7. Radiation sensor connected to robot processor.

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